CATEGORIZING THE AGE GROUP AND MEASURING ACCURACY OF FUZZY MODEL

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ABSTRACT

The age group estimation can be done in many methods for each and every step in the process. To estimate the age group we can perform many methods for each and every step. In our proposed method we are estimating the age group after extracting the features in any one of the method and derives an algorithm. Based on that algorithm we created fuzzy model to classify the dataset and predict the age. In our paper the performance of fuzzy model is also evaluated. The different applications of age estimation are law enforcement, biometrics, security control, human computer interaction, crime detection.

Keywords: Fuzzy Model, Age Estimation, Feature Extraction, Prediction.

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1. INTRODUCTION

There is many methods to extract the key features from each database After extracting the face features from facial image the labelling of the age can be done by a class or by a set of sequential values. If the labelling is done through a class then it is solved through classification otherwise it is solved through regression. In our paper we are classifying, predicting and evaluating our proposed fuzzy model to estimate the age. The brief process is based on the derived algorithm first we split the data in to two subsets i.e. training data and test data by using stratified cross validation method. By using training data and test data we are classifying or predicting the age group using Fuzzy model and evaluation measures are considered by using confusion matrix. We can estimate the age through multi class classification or regression or a combination of both classification and regression. In fuzzy model after defining the membership function and deciding the descriptors our proposed model can categorize the age group.

After defining the membership function we can establish the relation between input variable and output variable. Then after forming the rule based we can evaluate the rules and then we can evaluate the strong rule.

2. LITERATURE SURVEY

2.1. Identification of the Facial Skin Region

Identify the skin region by using Hue Saturation Value colour model. We can identify the skin pixels by using the formulas of HSV model and Convert the skin region of RGB image into Grey scale image

2.2. Counting the Transition Count

With the help of 5X5 window extract the features of the image by identifying any one of the patterns or by local binary pattern, local direction pattern, and Local Ternary pattern. The extracted feature is in binary value. With that binary value we can count 0 transitions, 2 transitions, 4 transitions

2.3. Derive an Algorithm

By analysing the transition count of different facial image databases we can derive an algorithm

2.4. Data Splitting Methods

There are different data splitting methods. They are

a) Cross-Validation (CV) b) Bootstrap and Monte-Carlo Cross-Validation (MCCV) c) Bootstrapped Latin Partition (BLP) d) Kennard-Stone algorithm (K-S) and Sample Set Partitioning Based on Joint X - Y Distances Algorithm (SPXY). Our present research work uses Stratified cross validation is used to split train dataset and test dataset some different types of Cross Validation are

- Leave One Out Cross Validations (LOOCV)
- k-fold cross-validation
- Stratified Cross Validation
- Time Series cross validation

Our research paper works on Stratified Cross Validation to split the dataset into training dataset and test dataset

2.4.1. Stratified Cross Validation

It is similar to K-fold cross validation. Only difference is select that 25 data points such that it covers all classes belong to our dataset points. Similarly we have to perform 5 experiments on our 100 dataset points by selecting different 25 dataset points which includes all different class type instances.

2.5. Fuzzy Classifier

The classifier is an algorithm that classifies the given data and label to an object and also predicts the given tuple belongs to which class label. Feature vector describes the object descriptor.

2.5.1. Fuzzy Membership Function

Consider a Fuzzy set A where the set is determined as $\{(x, m(x)) | x \in X\}$ where x is an element, $m(x)$ is the membership function of set A and X is the universe of discourse. In fuzzy sets each element is mapped by membership function within the interval $[0,1]$ which can be represented as $m(x):X \rightarrow [0,1]$ where

$M(x)=1$ if x is totally in A; $M(x)=0$ if x is not in A; $0 < M(x) < 1$ if x is partly in A;

There are many fuzzy membership functions. Among them our research paper uses Triangular membership function

2.5.1.1. Triangular Membership Function

Let a, b, c are the three vertices to represent the x-coordinate of $m(x)$ in fuzzy set A.

a- lower boundary where membership degree is zero

c- upper boundary where membership degree is zero

b-the centre where membership degree is one

$m(x)=0$ if $x \leq a$; $m(x)=(x-a)/(b-a)$ if $a \leq x \leq b$; $m(x)=(c-x)/(c-b)$ if $b \leq x \leq c$; $m(x)=0$ if $x \geq c$;

Figure 1 Triangular Membership Function

2.6. The Confusion Matrix for Multiple Classes

To evaluate the performance of our fuzzy model we are using confusion matrix for multiple classes. The confusion matrix is a matrix where columns represent the predicted classes and rows represent the actual classes. The diagonal values are True Positive values for their respective class. The confusion matrix is used to measure the model performance. We are using Accuracy, Precision, Recall, F1 score are the performance measures based on confusion matrix. To select one of the models we have to use one of the performance measure based on the dataset points. To calculate those performance methods we have to know about the following terms

1) True Positive: True Positive (TP) are the values which are correctly identified for each class i.e. When both actual class of the data point and the predicted was true.

2) True Negatives: True Negatives (TN) are correctly rejected for a given class i.e. when both actual class of the data point and the predicted was false.

3) False Positives: False Positives (FP) are incorrectly identified for certain class i.e. when the actual class of the data point is false and predicted as true

4) False Negatives: False Negatives (FN) are incorrectly rejected for certain class i.e. when actual class of the data point was true and predicted as false.

The performance measures based on confusion matrix are

2.6.1. Accuracy

It is calculated as total no of correct predictions divided by total number of data points
 $\text{Accuracy} = \frac{TP_A + TP_B + \dots + TP_N}{\text{total no of data points}}$.

2.6.2. Precision

The output of the precision is it returns only relevant instances of a given model. The formula of the precision for a given class A is

$\text{Precision } P(A) = \frac{TP_A}{TP_A + FP_A}$.

So Average Precision = $P(A) + P(B) + \dots + P(N)/N$

2.6.3. Recall or Sensitivity

The output of the sensitivity is to identify all relevant instances. The formula of the sensitivity for a given class A is

$\text{Recall } R(A) = \frac{TP_A}{TP_A + FN_A}$. So Average Recall = $R(A) + R(B) + \dots + R(N)/N$.

2.6.4. F1 Score

The output of the F1 score is the harmonic mean of recall and precision. Single metric that combines recall and precision using the harmonic mean

$\text{F1 Score} = \text{Harmonic Mean (Precision, Recall)}$

$\text{F1 Score} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$

3. PROPOSED METHOD

Our proposed method is designed into two portions. The first portion tells us about inputting the each input image at a time .The second portion tells us about inputting the set of facial database images

3.1. First Portion

Step1. Input the original face image

Step2. Identify the skin region of face

Step3. Now convert the RGB face image into grey scale image.

Step4. Extract the features of the image by using the following methods. Those are two types of methods. First method consists of the following methods a) LBP method b) LTP method c) LDP method. Second method consists of the following patterns a)V and Inverted V pattern b)Diamond pattern c)Right angular and left angular Pattern

Step5.Count the number of 0 transitions and also count the number of 4 transitions for the given image

3.2. Second Portion

Facial database

images

i/p

o/p

Finds out 0 transition and 4 Transition for each image

Database which contains counts of 0 & 4 transitions of each and every image

FIRST PORTION

OUTPUT DATABASE

Figure 2 Block diagram, of proposed method

- Step1.The five different types of databases are given as input to the first portion one by one.
- Step2.The output of the FIRSTPORTION is the database which contains the output of each and every image
- Step 3.The database is split into two datasets .One is training dataset and other is Test data set by using Stratified cross validation method.
- Step 4.With the analysis of training dataset we can derive an algorithm.
- Step5.For that derived algorithm we have to detect what are the inputs and outputs
- Step 6.By using the inputs and outputs of an algorithm we are creating Fuzzy model
- Step7.Now the fuzzy model is validated by taking each Test data set as an input
- Step8.The Fuzzy model is evaluated its performance by calculating the F1 score and Accuracy.

3.3. Fuzzy Model

Figure 2 Block diagram

Table 1 Rule based form resultant Matrix

AGE	VS	S	M	L	VL
VS	Senior	Middle	Child	Senior Citizen	Child
S	Senior	Middle	Senior Citizen	Young	Young
M	Middle	Middle	Senior Citizen	Senior Citizen	Young
L	Senior	Middle	Middle	Senior Citizen	Young
VL	Senior	Middle	Senior Citizen	Senior Citizen	Young

Membership function for (0) transition count for first input variable(x):

(1). $M_{VS(0)}(X) = (734-x)/734$ if $0 \leq x \leq 734$; (2). $M_{S(0)}(X) = (x-0)/734$ if $0 \leq x \leq 734$ & $(837-x)/(837-734)$ if $734 \leq x \leq 837$; 3. $M_{M(0)}(X) = (x-734)/(837-734)$ if $734 \leq x \leq 837$ and $(909-x)/(909-837)$ if $837 \leq x \leq 909$; 4. $M_{L(0)}(X) = (x-837)/(909-837)$ if $837 \leq x \leq 909$ and $(1103-x)/(1103-909)$ if $909 \leq x \leq 1103$; 5. $M_{VL(0)}(X) = (x-909)/(1103-909)$ if $909 \leq x \leq 1103$

Membership function for the (0+4) transitions for second input variable(y)

1. $M_{VS(0+4)}(y) = (1050-y)/1050$ if $0 \leq y \leq 1050$
2. $M_{S(0+4)}(y) = (y-0)/1050$ if $0 \leq y \leq 1050$ and $(1085-y)/(1085-1050)$ if $1050 \leq y \leq 1085$
3. $M_{M(0+4)}(y) = (y-1050)/(1085-1050)$ if $1050 \leq y \leq 1085$
 $= (1145-y)/(1145-1085)$ if $1085 \leq y \leq 1145$
4. $M_{L(0+4)}(y) = (y-1085)/(1145-1085)$ if $1085 \leq y \leq 1145$
 $(1400-y)/(1400-1145)$ if $1145 \leq y \leq 1400$
5. $M_{VL(0+4)}(y) = (y-1145)/(1400-1145)$ if $1145 \leq y \leq 1400$

Membership function for Age group category for output variable (z)

Different age group categories are 1. Childhood 2. young Age (13-25years)

3. Middle age (26-40years) 4. Senior age (40-60years) 5. Senior Citizens (more than 60 years)

1. $M_{childhood}(z) = (13-z)/13$ if $0 \leq z \leq 13$;
- (2). $M_{young}(z) = (z-0)/13$ if $0 \leq z \leq 13$; $(26-z)/(26-13)$ if $13 \leq z \leq 26$;
- (3). $M_{Middle}(z) = (z-13)/(26-13)$ if $13 \leq z \leq 26$; $= (40-z)/(40-26)$ if $26 \leq z \leq 40$;
- (4). $M_{Seniors}(z) = (z-26)/(40-26)$ if $26 \leq z \leq 40$
 $(80-z)/(80-40)$ if $40 \leq z \leq 80$;
5. $M_{Senior\ citizens}(z) = (z-40)/(80-40)$ if $40 \leq z \leq 80$

4. RESULTS AND DISCUSSION

Table 2 Membership function for 0 transition & (0+4) transitions

Test dataset (0),(0+4) transition	VS	S	M	L	VL		VS	S	M	L	VL
461	vs	s					0.371	0.628			
1192				L	VL					0.815	0.1843
730	vs	s					0.00545	0.9945			
1266				L	VL					0.5254	0.4745
734	vs	s	m				0	1,1	0		
1272				L	VL					0.5019	0.4980
821		s	m					0.15539	0.8446		
1380					VL						0.9215
841	vs	s					-0.1457	1.1457			
1051		S	M					0.9714	0.0285		
899			m	l					0.1388	0.8611	
1083		S	M					0.0571	0.9428		
913				l	vl					0.9793	0.0206
877		S	M					0.1647	0.8352		
1006				l	vl					0.5	1
1043	VS	S					0.0066	0.9933			
1025				l	vl					0.4020	0.5979
1085		S	M	L				0	1	0	
1192				-	-		-----	-----	-----	-----	-----
1142			M	L					0.05	1	

4.1. Form a Rule Base and Evaluate the Rules in the Table

From the above table we are calculating the membership function values(vs, s, m, l, vl) for 0 transition count and also calculating membership function values(VS,S,M,L,VL) for (0+4) transition count. Some functions evaluate very small and small membership functions and some functions evaluate medium, large, very large membership functions. Based on those values different rules are generated for each and every dataset.

After generating the rules for each data set the maximum value is considered. That value is used to calculate the output value.

Resultant Matrix

The above model is to categorize the age groups by taking the training dataset as an input. The above model produces the resultant matrix as shown below by using the above model. we will find out the membership functions for input variables for (0) transitions and (0+4) transitions. Next we substitute each and every test data set values in those membership functions

Table 3 Strength rules for each dataset.

Lac(0) Rac(0+4)	R1	R2	R3	R4	R5	R6	MAX
461 1192	0.37	0.1843	0.628	0.1843			0.628
730 1266	0.0054	0.0054	0.5254	0.4745			0.5254
734 1272	0	0	0.5019	0.4980	0	0	0.5019
821 1380	0.8446	0.1553					0.8446
841 1051	-0.1457	-0.1457	0.9714	0.0285			0.9714
899 1083	0.0571	0.1388	0.0571	0.8611			0.8611
913 877	0.1647	0.8352	0.0206	0.0206			0.8352
1006 1043	0.0066	0.5	0.0066	0.9933			0.9933
1025 1085	0	0.4020	0	0	0.5979	0	0.597
1192 1142	1						1

4.2. Calculate Z Value

The z value is calculated by taking the maximum value of the above table and equalizing that value to the output membership functions. Then we can predict particular age for each and every data set .we is obtaining the z value by using defuzzification technique.

Table 4 Predicting age by Deffuzification

Lac (0) Rac(0+4)	Z Vaue	Predicted Age Group	Actual Age group
461 1192	12.775	Child	child
730 1266	13	Young/child	child
734 1272	13	Young/child	young
821 1380	13	Young/child	young
841 1051	26.0143	Middle/senoirs	Middle age

Lac (0) Rac(0+4)	Z Vaue	Predicted Age Group	Actual Age group
899	26.0695	Middle/Seniors	Middle age
1083			
913	73.408	Seniors/senior citizen	Seniors
877			
1006	40	Seniors	Seniors
1043			
1025	63.916	Seniors/seniorcitizens	Senior citizen
1085			
1192	80	seniorcitizen	Senior citizen
1142			

FN(1)=0; FN(2)=0;FN(3)=0 ; FN(4)=0; FN(5)=0

Table 5 Confusion Matrix

	Child	Young	Middle Age	Senior	Senior Citizen	Total
Child	2	0	0	0	0	2
Young	0	2	0	0	0	2
Mid Age	0	0	2	0	0	2
Senior	0	0	0	2	0	2
Senior Citizen	0	0	0	0	2	2
Total	2	2	2	2	2	10

TP=2; TP=2; TP=2; TP=2; TP=2

FP=0 ; FP=0; FP=0; FP=0; FP=0

P (1) =1; P(2)=0.666;P(3)=1;P(4)=1;P(5)=1

4.3. Confusion Matrix for Multiclass

From the above table we can find out the accuracy model by using confusion matrix .The fuzzy model not gives us the boundary value, instead it gives us the range value. So for any fuzzy models hoping it gives us the cent percent accurate value if our rule based assumption is cent percent correct

4.5. Different Performance Measures

1) ACCURACY: For balanced data accuracy gives good results. If accuracy is high our model is good. But finding out the accuracy for imbalanced data misleads performance. The TP gives us correct classifications.

$$\text{Accuracy} = \frac{TP1+TP2+TP3+TP4+TP5}{\text{Total no of Classifications}}$$

$$= \frac{2+2+2+2+2}{10} = \frac{9}{10} = 1$$

2) PRECISION:

precision (Class 1)= $P(1) = TP1/(TP1+FP1)$

$P(1) = 2/2+0 = 1$; $p(2)=2/2+0=1$;

$P(3)=2/2+0 = 1$; $P(4)=2/2=1$; $P(5)=2/2=1$;

So Average Precision= $(1+1+1+1+1)/5 = 1$

3)RECALL:

Recall(Class1)= $R(1)=TP1/(TP1+FN1)$

$R(1)=2/2+0 = 1$; $R(2)=2/2+0 = 1$; $R(3)=2/2=1$;

$R(4)=2/2=1$; $R(5)=2/2=1$; So Average Recall= $(1+1+1+1+1)/5 = 1$

4) F1 SCORE:

F1 score= $2 * \text{Precision} * \text{Recall} / (\text{Precision} + \text{Recall})$

$= 2 * 1 * 1 / (1+1)$;

$= 1$

5. CONCLUSION

The present paper evaluates the performance of our Fuzzy model from 0 transition count and 0+4 transition count. The Fuzzy model classifies the data and predicts the dataset. The accuracy of our proposed research work is 100% if our assumption table which is derived from algorithm is accurate. The Fuzzy model doesn't gives us boundary value rather it specifies the range of the value. So the models created by using fuzzy model produce excellent accuracy if our rule based assumption is accurate. The F1 score value for our proposed model is 1. The accuracy value for our model is good when the dataset in confusion matrix is balanced data. For imbalanced data the F1 score is the perfect measure. In Future we can use Fuzzy model as a classifier and predictor for not only in age grouping but also in other problems which we can categories.

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